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PEER LEARNING ON THE EDGE IN VEHICLES

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PEER LEARNING ON THE EDGE IN VEHICLES

ABSTRACT

A vehicle head unit may train a surround-view (SV) detection module to rectify distortions in fish-eye camera images of the surroundings of a vehicle by comparing the object (e.g., traffic signs, lane markings, etc.) detection results of the SV detection module with those of an advanced driver assistance system (ADAS) detection module (e.g., while the SV detection module and the ADAS detection module are detecting the same objects of the same scenery). The vehicle head unit may receive the object detection results of the ADAS detection module by using one or more communication processes. For example, the vehicle head unit may use the object detection results of the ADAS detection module as ground truth data for training the SV detection module. The vehicle head unit may then update parameters, weights, and/or the like of the SV detection module to decrease the difference between the object detection results of the SV detection module and ADAS detection module. In some examples, the vehicle head unit may send (potentially after anonymizing personally identifiable information) the updated parameters, weights, and/or the like of the SV detection module to a remote computing system (e.g., a cloud server) to train a machine learning model that implements SV detection modules. The machine learning model may be trained using the collective updated parameters, weights, and/or the like of multiple SV detection modules.

DESCRIPTION

The present disclosure describes training a surround-view (SV) detection module of a vehicle head unit to rectify distortions in fish-eye camera images of the surroundings of a vehicle (e.g., an automobile, a motorcycle, a bus, a recreational vehicle (RV), a semi-trailer truck, a tractor or other type of farm equipment, train, a plane, a boat, a helicopter, a personal transport vehicle, etc.) by comparing the object (e.g., traffic signs, lane markings, etc.) detection results of the SV detection module with those of an advanced driver assistance system (ADAS) detection module (e.g., while the SV detection module and the ADAS detection module are detecting the same objects of the same scenery). For example, the vehicle head unit may use the object detection results of the ADAS detection module as ground truth data for training the SV detection module. The vehicle head unit may then update parameters, weights, and/or the like of the SV detection module to decrease the difference between the object detection results of the SV detection module and ADAS detection module.

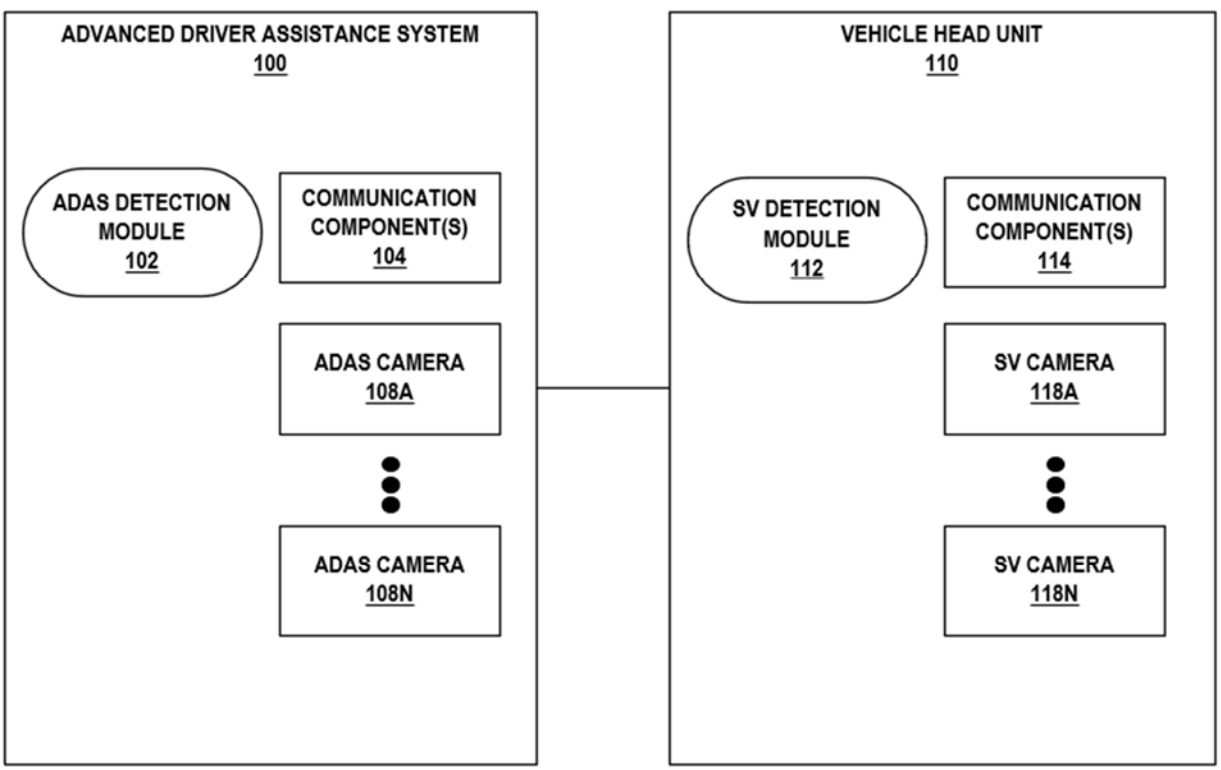

FIG. 1

FIG. 1 is a conceptual diagram illustrating a vehicle head unit 110 that trains a SV detection module 112 to rectify distortions in fish-eye camera images of the surroundings of a vehicle by comparing the object (e.g., traffic signs, lane markings, etc.) detection results of SV detection module 112 with those of an ADAS detection module 102. As illustrated by FIG. 1, vehicle head unit 110 may include SV detection module 112, SV cameras 118A-118N (collectively, “SV cameras 118), and communication components s 114.

Vehicle head unit 110 may represent an integrated head unit that controls vehicle head units, such as a detection system (e.g., a SV detection system, an ADAS, etc.), an audio system, a heating, ventilation, and air conditioning (HVAC) system, a lighting system (for controlling interior and/or exterior lights), an infotainment system, a seating system (for controlling a position of a driver and/or passenger seat), and the like. Vehicle head unit 110 may be included in an automobile, a motorcycle, a bus, a RV, a semi-trailer truck, a tractor or other type of farm equipment, a train, a plane, a drone, a helicopter, a personal transport vehicle, or the like.

Communication components 104, 114 may include wired communication devices capable of transmitting and/or receiving communication signals via a direct link over a wired communication medium (e.g., an Ethernet cable, a controller area network (CAN) bus, a universal serial bus (USB) cable, etc.). Additionally or alternatively, communication components 104, 114 may include wireless communication devices capable of transmitting and/or receiving communication signals such as a cellular radio, a 3G radio, a 4G radio, a 5G radio, a Bluetooth® radio (or any other PAN radio), an NFC radio, or a Wi-Fi™ radio (or any other WLAN radio). In some examples, communication components 104, 114 may be directly linked to each other over a wired communication medium (e.g., an Ethernet cable, a controller area network (CAN) bus, a universal serial bus (USB) cable, etc.), although wireless communication is also contemplated by this disclosure.

In general, a vehicle may include SV cameras that are fish-eye cameras (or, in other words, cameras with fish-eye camera lenses) to capture wide-angle images of the surroundings of the vehicle. In addition, the vehicle may include ADAS cameras to also capture images of the surroundings of the vehicle. The ADAS cameras may have lenses other than fish-eye camera lenses, such as a standard lens, a wide-angle lens, a telephoto lens, and/or the like. Cameras with lenses other than fish-eye lenses may capture images that are less distorted than fish-eye camera images. As a result, images captured by cameras with lenses other than fish-eye lenses may be more suitable than fish-eye camera images for training a machine learning module to detect objects surrounding the vehicle.

In accordance with techniques of this disclosure, vehicle head unit 110 may train SV detection module 112 to rectify distortions in fish-eye camera images of the surroundings of a vehicle by comparing the object (e.g., traffic signs, lane markings, etc.) detection results of SV detection module 112 with those of ADAS detection module 102 (e.g., while the SV detection module and the ADAS detection module are detecting the same objects of the same scenery). That is, vehicle head unit 110 may improve the performance of SV detection module 112 based on the object detection results of ADAS detection module 102. As discussed below in greater detail, vehicle head unit 110 may also operate in conjunction with a remote computing system (e.g., a remote server, which may represent an example of a cloud-based server) to train SV detection module 112.

In some examples, SV detection module 112 may be or include one or more artificial neural networks (also referred to as neural networks). A neural network may include a group of connected nodes, which also may be referred to as neurons or perceptrons. A neural network may be organized into one or more layers. Neural networks that include multiple layers may be referred to as “deep” networks. A deep network may include an input layer, an output layer, and one or more hidden layers positioned between the input layer and the output layer. The nodes of the neural network may be connected or non-fully connected.

In some examples, SV detection module 112 may represent one or more convolutional neural networks. In some instances, a convolutional neural network may include one or more convolutional layers that perform convolutions over input data using learned filters. Filters may also be referred to as kernels. Convolutional neural networks may be especially useful for vision problems (e.g., when the input data includes imagery such as still images or video). Thus, SV detection module 112 may perform convolutions over fish-eye camera images to rectify distortions in accordance with techniques described herein.

Vehicle head unit 110 may collect input data by using SV cameras 118. The input data (e.g., fish-eye camera images) received by SV detection module 112 may include imagery such as still images or video (e.g., a series of still images that are referred to as “frames”) captured by one or more of SV cameras 118. SV cameras 118 may be fish-eye cameras configured to provide a wide-angle, but distorted, view of the surroundings of a vehicle. For example, the distortion may be a barrel distortion where image magnification decreases with distance from the optical axis. As a result, the image may appear to be mapped around a sphere or barrel.

Responsive to receiving the input data including imagery such as still images or video captured by SV cameras 118, SV detection module 112 may output object detection results of SV detection module 112. For example, SV detection module 112 may detect traffic signs (e.g., the speed limit signs, traffic instruction signs, etc.), lane markings, traffic lights, vehicles, people, barriers, and the like present in the scenery of the imagery captured by SV cameras 118.

As shown in FIG. 1, ADAS 100 may include ADAS detection module 102. ADAS 100 may further include ADAS cameras 108A-108N (collectively, "ADAS cameras 108") and communication components 104, which may be similar if not substantially similar to communication components 114 except for any differences described herein. ADAS 100 may collect input data by using ADAS cameras 108. ADAS cameras 108 may have lenses other than fish-eye lenses that capture images that are less distorted than fish-eye camera images. Responsive to receiving the input data including imagery such as still images or video captured by ADAS cameras 108, ADAS detection module 102 may output object detection results of SV detection module 112. For example, ADAS detection module 102 may detect traffic signs (e.g., the speed limit signs, traffic instruction signs, etc.), lane markings, traffic lights, vehicles, people, barriers, and the like present in the scenery captured by ADAS cameras 108.

The object detection results of ADAS detection module 102 and SV detection module 112 may be more accurate than those of SV detection module 112 for various reasons. For example, ADAS detection module 102 may implement more sophisticated algorithms (e.g., image processing, pattern recognition, scene analysis, etc.) than those of SV detection module 112. Additionally, ADAS cameras 108 may use lenses that capture images that are less distorted than fish-eye images. Further, ADAS cameras 108 may be more powerful (e.g., have a higher resolution, more memory, more computationally powerful image processors, etc.) than SV cameras 118. Thus, the input data received by ADAS detection module 102 may be a more accurate representation of reality than the input data received by SV detection module 112. For example, the images or videos captured by ADAS cameras 108 may have a higher resolution, less distortion, and/or the like than the images or videos captured by SV cameras 118.

Because the object detection results of ADAS detection module 102 may be more accurate than those of SV detection module 112, vehicle head unit 110 may use the object detection results of ADAS detection module 102 as ground truth data for training the SV detection module 112. For example, SV detection module 112 may be trained using training data that includes example input data that has labels (e.g., object detection results) assigned by ADAS detection module 102. In such an example, SV detection module 112 may seek to optimize an objective function. The objective function may be or include a loss function that compares (e.g., determines a difference between) output data generated by SV detection module 112 from the training data and labels, which represent ground truth data, associated with the training data.

For example, if SV detection module and the ADAS detection module are detecting the same objects of the same scenery and the object detection results of ADAS detection module 102 and those of SV detection module 112 are different with respect to any detected objects, vehicle head unit 110 may determine that the object detection results identified by ADAS detection module 102 are true while the object detection results of SV detection module 112 are false. Vehicle head unit 110 may receive the object detection results of ADAS detection module 102 from ADAS 100 via communication components 114. Similarly, ADAS 100 may send the object detection results of ADAS detection module 102 to vehicle head unit 110 by using communication components 104.

Responsive to receiving the object detection results of ADAS detection module 102 from ADAS 100, vehicle head unit 110 may train SV detection module by updating parameters, weights, and/or the like of SV detection module 112 to potentially decrease the difference between the object detection results of SV detection module 112 and ADAS detection module 102. For example, if the object detection results of ADAS detection module 102 indicate that the speed limit sign of a scenery displays the number “65” and the object detection results of SV detection module 112 indicate that the same speed limit sign of the same scenery displays the number “35,” then vehicle head unit 110 may update parameters, weights, and/or the like of SV detection module 112 until the updated object detection results of SV detection module 112 indicate that the same speed limit sign of the same scenery results in the same object detection result of the number “65.” In this way, vehicle head unit 110 may optimize the objective function by decreasing the difference between the object detection results of SV detection module 112 and ADAS detection module 102.

In some examples, vehicle head unit 110 may send (potentially after anonymizing personally identifiable information) the updated parameters, weights, and/or the like of SV detection module 112 to a remote computing system (which is not shown in the example of FIG. 1 for ease of illustration purposes), such as a cloud computing system, to train a machine learning model. Similarly, multiple vehicle head units, including vehicle head unit 110, may send updated parameters, weights, and/or the like of corresponding SV detection modules to the remote computing system to train one or more machine learning models that implement SV detection modules, including SV detection model 112. In some examples, the remote computing system may train a machine learning model for each make and/or model of vehicle.

The remote computing system may be any suitable remote computing system, such as one or more desktop computers, laptop computers, mainframes, servers, cloud computing systems, virtual machines, and the like, capable of sending and receiving information from vehicle head unit 110 (e.g., via communication components 104, 114). In some examples, the remote computing system may represent a cloud computing system that provides one or more services. That is, in some examples, the remote computing system may be a distributed computing system. One or more vehicle head units (e.g., vehicle head unit 110) may access the services (e.g., to download the parameters, weights, and/or the like of the one or more machine learning models that represent SV detection modules, such as SV detection module 112) provided by the remote computing system. While described herein as being performed at least in part by vehicle head unit 110, any or all techniques of the present disclosure may be performed by the remote computing system, which may be a cloud computing system or any other type of remote computing system (which is not shown in the example of FIG. 1 for ease of illustration purposes).

One or more advantages of the techniques described in this disclosure include increasing the accuracy of SV detection modules, which may increase vehicle and road safety (e.g., by more accurately identifying traffic signs, nearby vehicles, pedestrians, etc.). In some examples, the techniques may even compensate for damage to SV cameras 118. For example, even if SV cameras 118 becomes slightly dislodged due to wear and tear, vehicle head unit 110 may still train SV detection module 112 until the object detection results of SV detection module 112 are the same as those of ADAS detection module 102. Another advantage includes reducing the resources (e.g., time, hardware resources, human resources, etc.) for training SV detection modules.

A brief overview of example machine-learned models and associated techniques has been provided by the present disclosure. For additional details, readers should review the following references: Machine Learning A Probabilistic Perspective (Murphy); Rules of Machine Learning: Best Practices for ML Engineering (Zinkevich); Deep Learning (Goodfellow);

Reinforcement Learning: An Introduction (Sutton); and Artificial Intelligence: A Modern Approach (Norvig). It is noted that the techniques of this disclosure may be combined with any other suitable technology or combination of technologies, including those listed as references below.

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